Generative Adversarial Network for Super-Resolution and Image Distortion Correction

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אפקה
המכללה האקדמית להנדסה בתל אביב

Introduction

Generative Adversarial Networks (GANs): GANs consist of a generator and a discriminator that work in opposition, with the generator creating fake images and the discriminator distinguishing between real and fake images.

The goal is to improve the generator until it can produce realistic images that the discriminator cannot distinguish from real images.

Objective

Enhancing low-resolution images and correcting distortions, particularly focusing on real-world images like US license plates.

Project Goals

1. Develop a deep learning model capable of performing super-resolution tasks.
2. Improve image quality by enhancing model performance, specifically addressing distortions.
3. Apply denoising techniques to reconstruct high-quality images from distorted inputs.

Methodology

Data Description:

DIV2K Dataset:

1,000 high-resolution images split into training, validation, and test sets.

US License Plates Dataset:

4,462 images, cleaned to 750 training images and 108 test images.

Data Preprocessing:

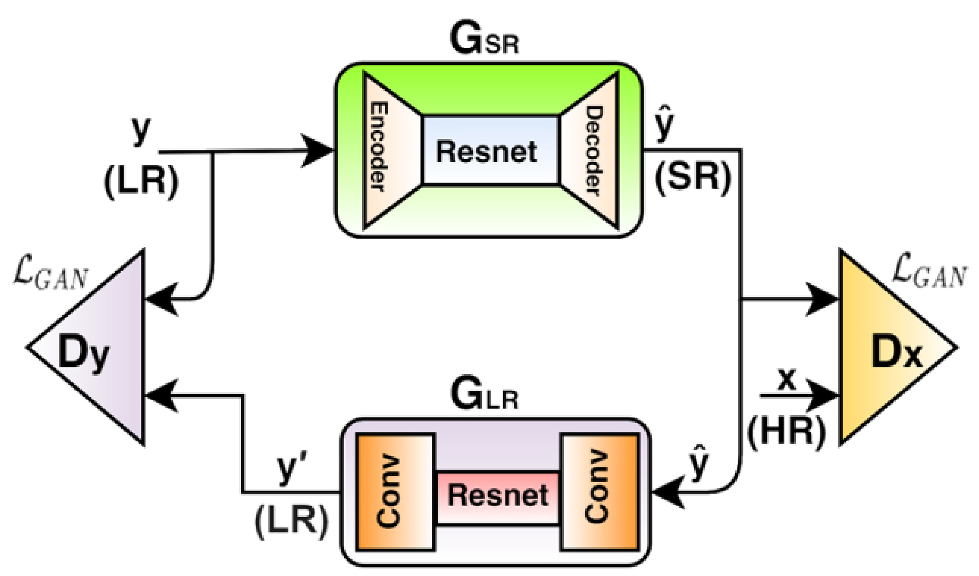
Downsampling: Images resized using BICUBIC distortion to maintain detail.

Dimensional Distortion: Rotation matrix applied to simulate spatial rotation around the Y-axis.

Training:

Hyperparameters: Learning rate, batch size, optimizer (Adam), and number of epochs tailored to ensure stability and efficiency.

General Architecture



Experiments

Experiment 1: Training on license plate images without distortion.

Experiment 2 & 5: Using a pre-trained model on the DIV2K dataset for undistorted license plates.

Experiment 3 & 4: Training on distorted images with different pre-training strategies, including the integration of DIV2K data.

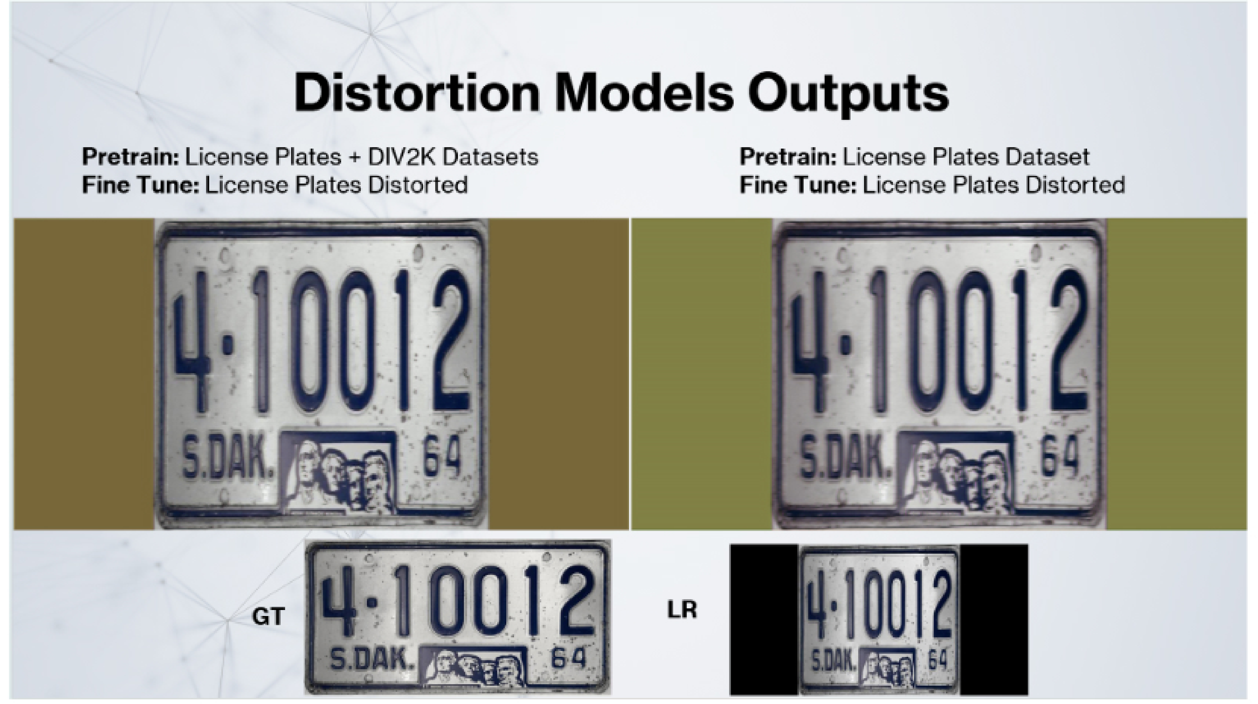
Results

Our model yielded the best results with a PSNR value of 40.4, SSIM of 0.992 and LPIPS of 0.0072 for super resolution without distortion (Experiment 2). For distortion, the model trained on the license plates and DIV2K datasets didn't produce great results both visually (LPIPS) and for PSNR and SSIM.

When trying to fix distortions, the model did not produce great results.

The Results + Best Model

Experiment	Distortion	Model	PSNR ↑	SSIM ↑	LPIPS ↓	Result Output
1	X	Our Model	38	0.985	0.013	
2	X	Our Model	40.4	0.992	0.0072	
3	V	Our Model	11.68	0.348	0.657	
4	V	Our Model	24	0.88	0.119	
5	X	Article Model	25.95	0.735	0.255	



Conclusions

1. Training using the DIV2K dataset on the weights of the model trained on the license plates dataset improved model performance and generalization.

2. Training on 3600 images of license plates, both high and low resolutions, proved that in this case, the quality of the data is more important than a larger dataset.

3. The model did not prove to be effective when handling distortions such as the rotated license plates. The model still managed to perform the super resolution tasks well but failed to reconstruct the rotated license plate to its original form.

4. The amount of resources available for building and training a model must be taken into consideration when bulding the model and the proper pre-processing should be made for the training process.